

Sub. B1:

Score  
 $\Delta$  Varied

1. A load indicator for an electric motor, comprising a first means (II, IU, CPU) for repeated determination of the motor load, a second means (CPU) for comparing the current motor load, as determined by the first means, with a preset load limit, and a third means (CPU, PP) for indicating that the current motor load exceeds the load limit, characterised by a means (T, CPU) for initiating a presetting of the load limit as the current motor load changed by a predetermined deviation value stored in the load indicator, said initiating means being adapted to be actuated as the motor runs in normal operation.
2. A load indicator as claimed in claim 1, characterised in that the deviation value is stored as a percentage which, multiplied by the nominal power of the motor, yields the actual deviation value.
3. A load indicator as claimed in claim 1, characterised in that the deviation value is stored as a percentage which, multiplied by the current load, yields the actual deviation value.
4. A load indicator as claimed in claim 1, characterised in that deviation value is stored as a fixed value.
5. A load indicator as claimed in ~~any one of claims 1-4~~ <sup>Claim 1</sup>, characterised in that the initiating means (T, CPU) is adapted to preset two deviation values which represent deviations in the same direction from the motor load in normal operation.
6. A load indicator as claimed in claim 5, characterised by a means (1) for determining the direction of deviation.
7. A load indicator as claimed in ~~any one of claims 1-4~~ <sup>Claim 1</sup>, characterised in that the initiating means (T, CPU) is adapted to preset two deviation values

ohj

Claim 1  
~~any one~~

Claim 1  
any-one

Claim 1  
n any one

Current  
sensors

$\{ \mathbf{u}_i^{(k)} \}_{i=1}^n$  and  $\{ \mathbf{v}_i^{(k)} \}_{i=1}^n$  are the left and right singular vectors of  $\mathbf{A}^{(k)}$ , respectively, and  $\sigma_i^{(k)}$  are the singular values of  $\mathbf{A}^{(k)}$ . The singular value decomposition (SVD) of  $\mathbf{A}^{(k)}$  is given by  $\mathbf{A}^{(k)} = \mathbf{U}^{(k)} \mathbf{\Sigma}^{(k)} \mathbf{V}^{(k)T}$ , where  $\mathbf{U}^{(k)} = [\mathbf{u}_1^{(k)} \dots \mathbf{u}_n^{(k)}]$ ,  $\mathbf{\Sigma}^{(k)} = \text{diag}(\sigma_1^{(k)}, \dots, \sigma_n^{(k)})$ , and  $\mathbf{V}^{(k)} = [\mathbf{v}_1^{(k)} \dots \mathbf{v}_n^{(k)}]$ . The singular value decomposition (SVD) of  $\mathbf{A}^{(k)}$  is given by  $\mathbf{A}^{(k)} = \mathbf{U}^{(k)} \mathbf{\Sigma}^{(k)} \mathbf{V}^{(k)T}$ , where  $\mathbf{U}^{(k)} = [\mathbf{u}_1^{(k)} \dots \mathbf{u}_n^{(k)}]$ ,  $\mathbf{\Sigma}^{(k)} = \text{diag}(\sigma_1^{(k)}, \dots, \sigma_n^{(k)})$ , and  $\mathbf{V}^{(k)} = [\mathbf{v}_1^{(k)} \dots \mathbf{v}_n^{(k)}]$ .